

Choice experiments with facial expression analysis: How do emotions affect wine choices?

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ARTICLE INFO

JEL classification:

D91
D11
D12
APA: 3900
3920
3 940

Keywords:

Wine-evoked emotions
Facial expression analysis
Discrete choice experiment
Organic wine
Experience
Credence attributes
Wine choice

ABSTRACT

In this paper, we assess the role of emotions in choices. We elicited emotions using an innovative facial expression analysis approach, comparing the results to those from a traditional hedonic liking scale. To this end, we conduct an experiment combining surveys and actual wine tasting. The results show a positive and significant relationship between positive emotions (joy), positive experiences (valence), and wine choices, especially in the case of wines with credence attributes (organic and selected vintage organic wines). Moreover, we conclude that facial recognition mechanisms can be useful to elicit evoked emotions and provide complementary information to the traditional liking scales to better understand decision making.

1. Introduction

Traditional economic models assume that consumers behave rationally to maximize their utility when making choices. This theory of reasoned action (Stanovich and West, 2000) is applied to many public policies (e.g., resource allocation decisions, taxation, subsidies, public health policies) and market strategies (e.g., price formation, fixation, and change; consumer demand; marketing). However, research has illustrated that consumers are not fully rational and that many behaviors are intuitive rather than reasoned or planned (Ekman, 2007; Kahneman, 2003; Keltner and Lerner, 2010; Keltner et al., 2014; Köster, 2009; Loewenstein et al., 2001). Emotions can affect decision-making, inducing behavioral biases (Schunk and Betsch, 2006) or improving decision-making performance (Hopfensitz and Mantilla, 2019).

During the mid-1980s, research on the role of emotions in complementing cognitive theories became more predominant, explaining more mysteries of consumer choice behavior (Hansen and Christensen, 2007; van Raaij, 2008). However, the role of

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emotions in behavior has been not effectively addressed in neoclassical theory because, among other reasons, emotions have been perceived as unimportant or unpredictable (Elster, 1996, 1998; Hansen et al., 2004).

New applications in behavioral economics (Kőszegi, 2006; Loewenstein and Lerner, 2003; Loewenstein, 2000; Rick and Loewenstein, 2008), psychology (Keltner and Lerner, 2010; Lerner et al., 2015), and neuroscience (Phelps et al., 2014) have demonstrated the important role of emotions in economic decision-making processes. Loewenstein (2000) illustrated that emotions are determinant drivers of behavior and are predictable. Kahneman described two complementary ways of making decisions: rationally and emotionally (Kahneman, 2003). He reported that people make decisions by unconsciously consulting their emotions (Kahneman, 2011). Hence, the role of emotions in the decision-making process is important and influential (Cherchi and de Dios Ortúzar, 2006).

Neuroeconomics has contributed to the understanding of the drivers of the consumers' decision-making process (Glimcher et al., 2009), especially by identifying the specific parts of the brain activated by emotions and measuring emotions with positron emission tomography (PET) and functional magnetic resonance imaging (fMRI) scans (Hansen and Christensen, 2007). However, despite these advances regarding the role of emotions in decision-making processes, little is known about how consumer choices are influenced by emotions, especially in multi-attribute choices. Elster (1998) considered attempts to understand how emotions influence behavior as insufficient and highlighting the need for more research (Daly and Hess, 2011).

There is a particular need for research focusing on how to measure emotions. Emotions are usually measured by self-reported measures, which are subject to various problems, including social desirability bias and difficulty in verbalizing emotions (Kaneko et al., 2018). Very few studies (Danner et al., 2014; He et al., 2016) have used implicit methods to measure product-evoked emotions. Results based on implicit methods – early autonomic nervous system (ANS) responses and facial expressions – were associated with relatively fast arousal emotions. However, Danner et al. (2014) and He et al. (2016) did not explore or analyze the relationship between evoked emotions and product choices. As pointed out by Niimi et al. (2019), new directions to measure emotions require the investigation of new tools, such as physiological measures (mainly, electro-dermal activity), and facial expressions. In our literature review, we did not find any study that measures evoked emotions using facial expressions in a research context of product choices (Parent, 2012).

These research gaps motivated us to assess the role of immediate product-evoked emotions on wine-purchasing decisions in an experimental setting. We take advantage of a unique experimental setting by combining two approaches to measuring emotions, sophisticated facial recognition technologies, and the classical hedonic score rating (Seo et al., 2004). Moreover, our research focuses on the role of both, valence and specific emotions in the decision-making process in a DCE context (Swait and Louviere, 1993). Furthermore, we tested whether the role of emotions is different by product, looking at their importance on the choice of credence goods (organic or selected vintage organic wines) or experience attributes (conventional wine).

2. Background literature

According to Rick and Loewenstein's (2008) review, both expected and immediate emotions influence economic behavior. Expected emotions are anticipated feelings about the consequences of decisions, and they are experienced after making a choice. Immediate emotions are experienced at the moment of making a decision, and they are categorized into two types: (1) integral immediate emotions, which are feelings about the consequences of a decision experienced at the moment of that choice decision, and (2) incidental emotions, which are also experienced at the moment of the decision but evoked by other sources unrelated to that decision. Rick and Loewenstein's (2008) review showed how considering the role of expected emotions rectified many inconsistencies of the basic axioms (monotonicity, transitivity, etc.) assumed by the economic models of risky decision-making, intertemporal choice, and social preferences. They also illuminated the role that both integral and incidental immediate emotions can potentially play in explaining behavioral phenomena. Rick and Loewenstein (2008) concluded that expected emotions receive far more research attention than immediate emotions and highlighted the need for more research on the role of immediate emotions in the production of behavior. Loewenstein (2000) warned that economists have mostly investigated expected emotions (regret, disappointment), while psychologists have been interested in immediate emotions. Loewenstein et al. (2001) reported that, together with expected emotions, immediate emotions should also be involved in decision-making models.

From the empirical perspective, some studies (Dalenberg et al., 2014; Gutjar et al., 2015; Thomson et al., 2010) have focused on the role of immediate product-evoked emotions in product choices. Gutjar et al. (2015) used a questionnaire deploying the EsSense Profile method to test whether emotional responses to intrinsic (sensory) and extrinsic (packaging) cues predict actual product choices. They found that emotions motivated by intrinsic and extrinsic product properties were different and that combining evoked emotions and liking ratings improved predictions of consumers' choice. Dalenberg et al. (2014) used a verbal method and a non-verbal method (EsSense Profile and PrEmo, respectively) to test whether food-evoked emotions improve food choice prediction. They demonstrated that food-evoked emotions overcame traditional perceived liking measures in predicting food choices, although the best predictions were made after combining both measures. Moreover, they showed that non-verbal (PrEmo) food-evoked emotions better predict food choices than verbal (EsSense Profile) food-evoked emotions. Thomson et al. (2010) analyzed the role of product-evoked emotions, measured using an appropriate lexicon of conceptual descriptors, in consumers' food choices in a best-worst scaling task. They suggested that considering food-evoked emotions would improve understanding of consumer food choices.

The economic theory of information categorizes goods into three groups: search, experience, and credence goods (Darby and Karni, 1973; Nelson, 1970). The food and wine market contain the three, according to their information content. Nelson (1970) distinguished between *search qualities* (those characteristics that are observable prior to consumption and identified by inspection before purchase; for example the color of wine) and *experience qualities* (identified only after the purchase and enjoyment of the good in question, for example the taste), and Darby and Karni (1973) identified a third category called *credence qualities* (cannot be judged even after

consumption, as information is even missing after consumption; for example, the non-use of pesticides in the production of organic wines). Niimi et al. (2019) postulated that emotion profiles can differ, even for equally liked wines. We test whether emotions play a different role depending on the type of wine (Schade et al., 2012).

We find that facial recognition methods sometimes outperform classical hedonic ratings, providing additional information beyond linking; and hence, these may be recommended. We also find a positive relationship between positive emotions (joy), positive experience (valence), and the choice of wines with credence attributes (organic or selected vintage organic wines). Nevertheless, despite existing efforts, understanding the role of emotions in choices remains challenging (Zeelenberg and Pieters, 2006).

3. Material and methods

3.1. Consumer survey

We analyzed consumers' preferences in the context of regular wine purchases in Barcelona. A survey, containing a labeled discrete choice experiment (DCE), combined with a blinded wine tasting, was conducted among 178 regular red wine drinkers. Participant recruitment was carried out by a research recruitment agency. Two similar groups of consumers were recruited, and each was representative of the population of Barcelona in terms of sex and age. All participants were responsible for their household's food purchasing, had lived in Barcelona for at least one year, and were regular (at least three times per month) buyers and drinkers of red wine.

Fig. 1 shows the main steps of the experiment. First, participants were welcomed, briefed about the objectives of the experiment, and asked to sign a consent form. Then, participants were informed about the type (young red wine), origin (Catalonia), grape variety (Tempranillo), and year of harvest (2017) of the wines. They were informed that the differences between the considered wines in the experiment were related to prices and the production systems. The differences between the three wine types (conventional, organic, and selected vintage organic wines) were then explained. Second, participants took part in a blind wine tasting where they tested (in a different order) the wines without receiving information about the wine types (production system). Third, they rated their actual liking of the wines using a nine-point hedonic scale of liking (1 = "very unpleasant" to 9 = "very pleasant"). Fourth, participants were informed about the wines' production system they tried and were asked to complete a survey containing a DCE.

Each respondent was required to answer a total of nine choice sets. In each choice set, participants were asked to choose from among three wine types (conventional, organic, and selected vintage organic) and an opt-out option (no choice). Fig. 2 provides an example of a choice set used in the experiment. The considered wines were experimental wines produced for this study and only differed in two attributes: the production system (conventional, organic, and selected vintage organic wines¹) and the corresponding prices (€3.50, €5.00, €6.50, €8.00). Three price levels were identified for conventional wines (€3.50, €5.00, €6.50) and for organic wines (€5.00, €6.50, €8.00) following market information. These price levels corresponded to the market prices of young red wines from Catalonia made with Tempranillo grapes. We also considered the context of usual consumption when we selected the price levels. We use a standard MNL-based efficient design for main effects employing Ngene software. Based on the lack of information (magnitude and sign) with respect to some specific parameters and their corresponding distributions, we have not employed priors.² Hence, we opted for a D_z efficient design (zero priors) with the minor D-error design possible among all. As a result, we obtain a D_z -efficient (D-error = 0.40) design with main effects only (no interactions) resulting in nine choice sets. In each choice set, participants were asked to choose between three typologies of wine and an opt-out option.

To check for hypothetical bias, half of the participants ($n = 89$) were randomly assigned to a non-hypothetical treatment (treatment group), and the other half ($n = 89$) to a hypothetical one (acting as a control group). Participants in the non-hypothetical treatment received €10 to be used in the experiment and were informed that at the end of the DCE task, a choice set would be randomly selected, and they would have to pay for a bottle of the wine originally selected on that choice set. Members of the control group did not receive money, nor were they required to buy a bottle of wine. Instead, they were given a brief talk explaining the problem of hypothetical bias in consumer studies and were invited to behave as they would in a shop or actual market setting.

3.2. Measurement of emotions

Concerning the measurement of emotions, we recruited a specialized private firm, which uses its technology to capture facial emotions and provides companies of different sectors (leisure and culture, hotels, banks, transport) with high-value information, including traffic at a store, the gender and age range of customers, wait and customer service times, emotional state, and emotional valence. Several systems based on the shape and movement of specific facial regions (facial muscle, edge of the mouth, eyes, and eyebrows) have been proposed for facial-expression-based emotion recognition (Ekman and Friesen, 1978; Yacoob and Davis, 1994).

¹ They are organic wines made with the best quality grapes of the 2017 harvest. A careful selection is done during the harvest to select the best quality grapes. It is a wine category typical from Spain.

² Although in this article we only present the results of the experiment conducted after tasting, this study also includes the same experiment before tasting the wines. It was a pre-post study, and we did not use different priors before and after wine tasting to assess the effect of taste. In other words, even if we have priors, they may be different before and after wine tasting, leading to different designs and difficulties in comparing the results. In the present work we focus on the decisions taken in a second experiment (after the wine tasting) because these are the only ones that could be affected by the measured emotions.

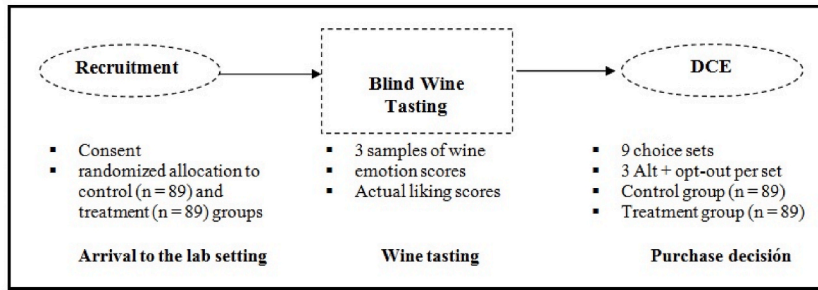


Fig. 1. Experiment protocol.

	Conventional wine	Organic wine	Selected vintage organic wine	None
Price	€3.5	€5	€8	None of the first three wines
I choose	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Fig. 2. Example of a purchase occasion (choice set).

The technology we used applies the Internet of Things by using sensors that record consumers’ facial emotions in two main streams: infrared and video. The combination of video plus infrared of great precision (FHD RGB + IR signals) provides a data stream with depth. From this information, “objects” are detected, which, following a pattern defined by applied algorithms, identify and differentiate the human body through a three-layer analysis: (1) human bodies: detection and differentiation of people against other objects or living beings; (2) extremities and joints: motion capture and follow-up; and (3) micro facial expressions: analysis of demographic profile and emotions. The sensors used for the present work incorporate two cameras (FHD RGB + IR) that recognize people while capturing subjects’ biometric features, collecting raw data that is automatically transferred to a data-processing server (cloud server) to extract participants’ emotions. The data processing works in the following way: once the raw biometric information is uploaded, several processes are run. These processes are responsible for identifying and extracting key signs on people’s faces. The key signs are, for example, the corners of the eyebrows, the tip of the nose, and the corners of the mouth. The aim is to detect and classify facial expressions. The facial coding system used is the highly accurate Facial Action Coding System developed by Carl-Herman Hjortsjö and adopted by Ekman and Friesen (1978) consists in a set of facial muscle movements associated with specific emotions. The basis of the facial coding system is to decompose facial expressions into a list of action units (basic facial movements) that can be combined to describe facial expressions. Several action units have already been identified (jaw drop, eyebrow drop, eyebrow raise, etc.), clinically validated and used to describe facial expressions (Parent et al., 2012). The technology used in this experiment captured movements from three hundred points to describe the seven basic emotions and valence.

The moments of interest selected for emotion analysis were the 10 s right after the wine tasting. We organized participants (Fig. 3) at three separate tables, with five participants per table. At each table, one sensor had been set up, since each given sensor can capture the facial emotions of five participants. The sensors take five measurements (five images) per second, which means that 10 recording seconds contain 50 measurements. For each individual, 50 measurements were recorded for each wine sample. We used the average values of facial emotions in the analysis. The use of this technology required compliance with the technical conditions related to the distribution and separation of the participants (see Fig. 3) to avoid the contagion of emotions. For coordination purposes, a signal was given to participants to start tasting each wine sample at the same time. Six sessions of 15 participants each (alternating between the control and treatment groups) were organized per day for two consecutive days in June 2018.

After this procedure, the seven basic emotions (anger, contempt, disgust, fear, joy, sadness, and surprise) and emotional valence

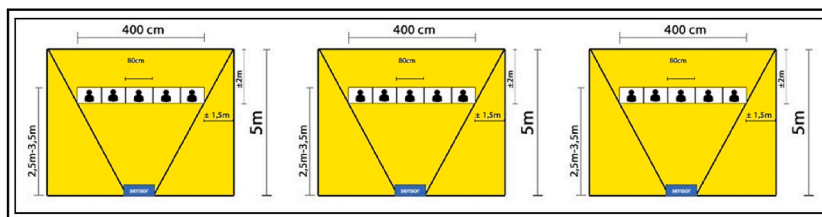


Fig. 3. Distribution of group members in the room.

were identified. Ekman et al. (1987) confirmed the universality of these seven facial expressions of emotions. The software also provides the intensity (0 = “not present at all” to 100 = “maximum intensity”) of the seven emotions. Emotional valence is a ratio between positive and negative emotions (Danner et al., 2014) that indicates the nature (positive or negative) and intensity (−100 = “very negative experience” to +100 = “very positive experience”) of the emotional experience. Elster (1998) has suggested using valence (positive and negative experiences) to describe emotions.

4. Model specification

Lancaster’s (1966) demand theory assumes that the utility derived from a given wine is the sum of the utilities provided by each of its attributes. According to the assumption of random utility theory, an individual will behave rationally in choosing the wine that provides them with the highest utility on each choice occasion. The utility derived from each alternative j by each individual n in choice situation t is expressed as follows (Revelt and Train, 1998):

$$U_{njt} = V_{njt} + \varepsilon_{njt} \quad (1)$$

where,

V_{njt} is the deterministic part and ε_{njt} is an error component.

Eq. (1) maybe estimated using a conditional logit model which assumes i) a linear association between U_{njt} and attribute parameters, ii) ε_{njt} is identically and independently distributed (i.i.d.) and, iii) preferences are homogeneous across individuals. However, consumers preferences for wine in Spain are rather heterogeneous. This is the reason why we discarded the use of conditional logit model.

4.1. The random parameter logit (RPL) model

The random parameter logit (RPL) model solves some of the previous assumptions relaxing the i.i.d. assumption and allowing preferences to be heterogeneous across individuals. It allows for different substitution patterns and for unobserved factors to be correlated over time because it overcomes the problem of the independence of irrelevant alternatives (IIA) assumption (Hensher and Greene, 2001). Hence, the utility function is expressed in the following way:

$$U_{njt} = \beta_n X_{njt} + \varepsilon_{njt} \quad (2)$$

where,

X_{njt} is a vector of observed variables and, β_n is a vector of parameters associated with X_{njt} , capturing an individual’s tastes or preferences for the attributes. These parameters are specific to the individual and vary in the population following the density $f(\beta_n|\theta^*)$, where θ are the moments of this distribution. ε_{njt} is a random term identically and independently distributed (i.i.d.) extreme value, and independent of β_n and X_{njt} .

$$V_{njt} = ASC_{nj} + \beta_p \times p_{njt} \quad (3)$$

where,

p_{njt} : is the price attribute, β_p : is the parameter of the variable Price. ASC_{nj} : are the alternative specific constants (where $j = 1, 2, 3$) which represent the labels (wine typologies): conventional wine (ASC1), organic wine (ASC2) and the selected vintage organic wine (ASC3).

Interactions of individuals’ variables (characteristics) with the alternative specific constants maybe included in the utility function to assess the sources of preferences heterogeneity.

$$V_{njt} = ASC_{nj} + \beta_p \times p_{njt} + \sum_{m=1}^m \delta_m (S_{nm} \times ASC_j) \quad (4)$$

where,

m is the number of individual variables chosen to identify the sources of preference heterogeneity. S_{nm} : are the individuals variables and δ_m is a vector of parameters associated with the interactions and show how the probability to choose any of the different wines shifts according to the individual variables.

4.2. Willingness to pay (WTP)

Specifying the price attribute independently from the vector of attributes, Eq. (2) maybe written in the following way:

$$U_{njt} = ASC_{nj} + \alpha_n p_{njt} + \varepsilon_{njt} \quad (5)$$

where,

Both ASC_{nj} and α are randomly distributed and specific to the individual capturing an individual’s tastes or preferences for the price and the labels (typologies of wine). ε_{njt} are the random terms following an extreme value distribution with a variance of $k_n^2 (\pi^2 / 6)$

which can vary over individuals and where k_n is the scale parameter for individual n . According to Train and Weeks (2005), dividing eq. (5) by the scale parameter would not affect the representation of preferences and the utility function maybe written as follows:

$$U_{njt} = (ASC_{nj} / k_n) + (\alpha_n / k_n)p_{njt} + (\varepsilon_{njt} / k_n) \tag{6}$$

And defining $\lambda_n = (\alpha_n / k_n)$, $c_{nj} = (ASC_{nj} / k_n)$ and $e_{njt} = \varepsilon_{njt} / k_n$, the utility function maybe written as follow:

$$U_{njt} = c_{nj} + \lambda_n p_{njt} + e_{njt} \tag{7}$$

where,

e_{njt} follow an extreme value distribution with a constant variance of $\pi^2/6$.

Eq. (7) represents the model in preference space (Train and Weeks, 2005). Knowing that WTP for an attribute represents the ratio of the non-cost attribute coefficient to the price coefficient ($w_{nj} = c_{nj} / \lambda_n$), eq. (8) represents the utility in WTP space (Train and Weeks, 2005).

$$U_{njt} = \lambda_n [w_{nj} + p_{njt}] + e_{njt} \tag{8}$$

We estimated the model both in preference space and WTP space using maximum simulated likelihood with 1 000 Halton draws (see details in Hensher and Greene, 2001; Revelt and Train, 1998). The Nlogit software was used for the estimations. We estimated a variety of RPL specifications where wine choices were modeled using the price (*Price*) and wine-specific constants (representing the labels): conventional wine (*ASC1*) and organic wine (*ASC2*) and the selected vintage organic wine (*ASC3*), and cross-products between the wine constants and several variables. All the models were estimated with a log-normal price parameter, and the wine-specific constants were random and normally distributed, as consumers could potentially like (positive preferences) or dislike (negative preferences) each of the three wine types. Inparticular, we estimated the following models.

M0: A baseline RPL model estimated using the combined (aggregated) data from the two groups (control and treatment groups). In this model, wine choices were modeled using the price (*Price*) and wine-specific constants: conventional wine (*ASC1*) and organic wine (*ASC2*) and the selected vintage organic wine (*ASC3*), as well as two cross-products between the wine constants and a dummy variable “*TREATMENT*” (1 if the participant was from the treatment group and 0 if otherwise).

M1: In this model, wine choices were modeled using the price, wine-specific constants and the cross-product (*HVALENCE_j*, where $j = 1, 2,3$) between the previously denoted wine-specific constants and the evoked valence measured through the face recognition software (*valence_j* > 0).

M2: In this model, wine choices were modeled using the price, wine-specific constants and the product between the wine constants and high actual liking scores (*LIKING_j* > 6) of each wine type (*HLIKING_j*, where $j = 1, 2,3$).

M3: In this model, wine choices were modeled using the price, wine-specific constants and both previous products (*HVALENCE_j* and *HLIKING_j*).

M4: In this model, wine choices were modeled using the price, wine-specific constants and the cross-products (*HJOY_j*, where $j = 1, 2,3$) and (*HCONTEMPT_j*, where $j = 1, 2,3$). *HJOY_j* represented the cross-products between the wine-specific constants (*ASC1*, *ASC2* and *ASC3*) and the *JOY_j* dummy variables (*JOY_j* > 5); *HCONTEMPT_j* represented the cross-products between the wine-specific constants and the *CONTEMPT_j* dummy variables (*CONTEMPT_j* > 5).

M5: In this model, wine choices were modeled using the same variables and products as in M4 but additionally included the cross product (*HLIKING_j*, where $j = 1, 2,3$).

Table 1
Descriptive statistics of the explanatory variables.

Sample	description	Control group (Hypothetical DCE)		Treatment group (Non-hypothetical DCE)		Sample	
		Mean	SD	Mean	SD	Mean	SD
89				89		178	
<i>Average age</i>	Age of participants	46.97	13.24	46.50	12.54	46.73	12.89
<i>FEMALE (%)</i>	1 if female; 0 otherwise	0.49	0.50	0.52	0.50	0.51	0.50
<i>HVALENCE1</i>	1 if <i>valence₁</i> > 0; 0 otherwise	0.09	0.29	0.13	0.34	0.11	0.31
<i>HVALENCE2</i>	1 if <i>valence₂</i> > 0; 0 otherwise	0.12	0.33	0.13	0.34	0.13	0.33
<i>HVALENCE3</i>	1 if <i>valence₃</i> > 0; 0 otherwise	0.12	0.33	0.13	0.34	0.13	0.34
<i>HLIKING1</i>	1 if <i>LIKING₁</i> > 6 >; 0 otherwise	0.25	0.43	0.35	0.48	0.30	0.46
<i>HLIKING2</i>	1 if <i>LIKING₂</i> > 6 >; 0 otherwise	0.42	0.49	0.45	0.50	0.43	0.49
<i>HLIKING3</i>	1 if <i>LIKING₃</i> > 6 >; 0 otherwise	0.44	0.50	0.52	0.50	0.48	0.50
<i>HJOY1</i>	1 if <i>JOY₁</i> > 5; 0 otherwise	0.12	0.33	0.20	0.40	0.16	0.37
<i>HJOY2</i>	1 if <i>JOY₂</i> > 5; 0 otherwise	0.17	0.16	0.16	0.36	0.16	0.37
<i>HJOY3</i>	1 if <i>JOY₃</i> > 5; 0 otherwise	0.12	0.33	0.19	0.39	0.17	0.37
<i>HCONTEMPT1</i>	1 if <i>CONTEMPT₁</i> > 5; 0 otherwise	0.29	0.45	0.22	0.42	0.26	0.44
<i>HCONTEMPT2</i>	1 if <i>CONTEMPT₂</i> > 5; 0 otherwise	0.26	0.44	0.35	0.48	0.30	0.46
<i>HCONTEMPT3</i>	1 if <i>CONTEMPT₃</i> > 5; 0 otherwise	0.27	0.44	0.36	0.48	0.31	0.46

M6: WTP for the different typologies of wine were estimated in WTP space to assure finite moments for WTP (Daly, 2012). Only the alternative specific constants and price are included in the model estimated in WTP space. No interaction term or cross product are included in this model.

5. Results

Eighty-nine individuals participated in each group (control vs. treatment). Table 1 shows the descriptive statistics of some characteristics of the sample. The percentages of women in the control (49%) and treatment (52%) groups were similar, $X^2(1, 178) = 0.20$, $p = 0.0653$. Furthermore, the *F-test* shows that there are no statistically significant differences in age across groups, $F(1, 175) = 0.06$, $p = 0.814$, namely, 46 years. Members of the two groups were representative of the local population in terms of sex and age (see Table 1). Thirty-three percent of each group belonged to households with a monthly income greater than €2,500. The average household size was of three persons in both groups. Forty percent of the control group had completed their university studies, while this level of study reached 25% of the members of the treatment group. The two groups were sufficiently similar to compare their behaviors.

Table 2 provides the means of the hedonic scores and emotional intensities. The selected vintage organic wine (6.07) received the highest hedonic liking score, followed by organic wine (5.87) and conventional wine (5.19). The three wines had negative valences, which means that, in general, participants did not like any of them. It should be noted that these wines were at their experimental stages produced only for this study. Emotions such as anger, fear, and sadness had means not far from zero, which implies that many participants did not express them clearly; while other emotions, such as surprise and contempt were more clearly denoted. We observe differences between consumers' self-reported perceptions (liking) and their real perceptions (emotions).

The descriptive analyses of the data from the DCE demonstrated many similarities in the preferences of the control and treatment groups. Fig. 4 illustrates the percentage of choices per wine type in the experiment. The selected vintage organic wine was the most preferred wine by members of both groups, followed by organic wine and conventional wine. The choice percentages for each wine were similar for the two groups and practically identical for the selected vintage organic wine. The percentage of participants selecting the opt-out option (selecting none of the wines) was also highly similar between the two groups.

Table 3 offers the results of all the estimated RPL models. Prior to the estimation, we have tested for differences in scales between both sub-samples, but those were not found statistically significant. Hence, our empirical results show evidence in favor of the statistical performance of pooled models, rather than separate models for the hypothetical versus real treatment. We checked preference regularity between the two groups (hypothetical vs non-hypothetical DCE). A validity test was conducted to check whether parameters are similar and whether data should be pooled (Louviere et al., 2000). We first tested possible scale parameters differences between the two groups following the procedure suggested by Campbell et al. (2008). The likelihood ratio test statistic (Swait and Louviere, 1993) was used and the results showed that the null hypothesis (equality of parameters) should not be rejected. We also confirmed the results of the preference regularity test using graphs as suggested by Louviere et al. (2000). For this reason, data from the two groups were pooled. Once we decided to pool the data, we also checked whether attributes should be specific or common for the two groups in the model estimated with pooled data following Cherchi and de Dios Ortúzar (2006). We calculated the ratios of the parameters (from the non-hypothetical sample)/parameters (of the hypothetical sample) and all the ratios are approximately equal 0.9. This means that the attributes should be common (generic) in the model with pooled data.

We estimated all the models stated in section 4 using the aggregated data from the two groups (control and treatment groups) and common attributes. Results are shown in Table 3. In all models, the price has a negative effect on choices, which is expected and in line with consumer theory and previous studies (Lockshin et al., 2006; Mann et al., 2012). In general, the selected vintage organic wine were the most preferred wine types (providing a higher marginal utility in all but one empirical specification), followed by the organic and conventional wines, in line with previous findings (Mann et al., 2012). The standard deviations of price parameter and the wine-specific constants are highly statistically significant, meaning that there is heterogeneity in the preferences for price and each typology of wine. This confirms the reason why we let the price parameter and the wine-specific constants to be random.

None of the included cross-products between wine type and the *TREATMENT* variable in model M0 were statistically significant. Thus, the condition to which each group (control or treatment) was subjected did not have a significant effect on participants' preferences for the wines. This result supports the descriptive analysis confirming the absence of hypothetical bias, which is similar to the findings reported by Carlsson and Martinsson (2001), but different from those of Lusk and Schroeder (2004). Consequently,

Table 2

Means of actual hedonic scores and emotion intensities.

	Conventional wine		Organic wine (OW)		Selected vintage OW	
	Mean	SD	Mean	SD	Mean	SD
Actual liking score (1 Very unpleasant to 9 Very pleasant)	5.19	0.02	5.87	0.02	6.07	0.02
Valence (-100 very negative experience to 100 very positive experience)	-11.35	0.23	-14.17	0.23	-11.20	0.25
Anger (0 not present at all to 100 maximum intensity)	0.37	0.01	0.56	0.02	0.59	0.02
Contempt (0 not present at all to 100 maximum intensity)	5.01	0.12	6.01	0.15	7.24	0.18
Disgust (0 not present at all to 100 maximum intensity)	9.24	0.20	11.99	0.26	10.43	0.21
Fear (0 not present at all to 100 maximum intensity)	0.27	0.01	0.16	0.01	0.51	0.06
Joy (0 not present at all to 100 maximum intensity)	5.15	0.15	3.46	0.10	4.30	0.16
Sadness (0 not present at all to 100 maximum intensity)	0.21	0.01	0.34	0.01	0.39	0.02
Surprise (0 not present at all to 100 maximum intensity)	3.05	0.08	2.82	0.08	3.69	0.14

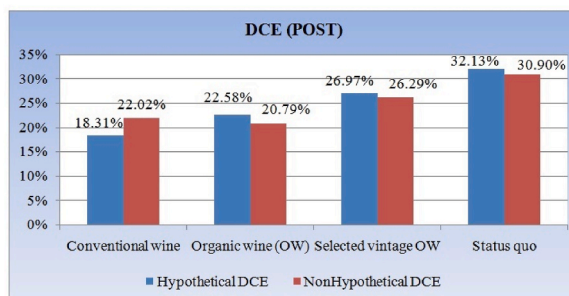


Fig. 4. Percentage of participants choosing wine alternatives after wine tasting (per group).

Table 3

Results of the estimated RPL models.

	RPL (M0)	RPL (M1)	RPL (M2)	RPL (M3)	RPL (M4)	RPL (M5)
<i>Parameters in utility functions</i>						
PRICE	-2.68*** ^a (0.159) ^b	-2.68*** (0.149)	-2.40*** (0.118)	-2.80*** (0.158)	-2.72*** (0.163)	-2.88*** (0.181)
ASC1 (CW)	10.98*** (0.776)	11.89*** (0.725)	11.12*** (0.711)	11.23*** (0.791)	12.00*** (0.763)	12.62*** (0.930)
ASC2 (OW)	14.22*** (0.920)	14.53*** (0.852)	14.24*** (0.829)	14.66*** (0.866)	14.26*** (0.951)	14.57*** (1.025)
ASC3 (SVOW)	14.40*** (0.872)	15.12*** (0.842)	14.58*** (0.868)	14.10*** (0.923)	15.32*** (0.951)	14.98*** (0.999)
<i>Standard deviations of random parameters</i>						
LsPRICE	1.30*** (0.163)	1.30*** (0.151)	1.53*** (0.179)	1.51*** (0.176)	1.36*** (0.169)	1.71*** (0.231)
NsASC1 (CW)	3.75*** (0.577)	3.74*** (0.572)	4.53*** (0.639)	5.06*** (0.642)	3.91*** (0.562)	4.76*** (0.685)
NsASC2 (OW)	4.727*** (0.579)	4.82*** (0.633)	4.29*** (0.554)	3.890*** (0.493)	5.43*** (0.662)	4.54*** (0.618)
NsASC3 (SVOW)	5.272*** (0.661)	5.79*** (0.667)	4.50*** (0.578)	5.42*** (0.583)	5.41*** (0.736)	4.47*** (0.615)
<i>Nonrandom parameters in utility functions</i>						
ASC1 * TREATMENT	0.80 (1.049)					
ASC2 * TREATMENT	0.553 (1.119)					
ASC3 * TREATMENT	0.84 (1.124)					
ASC1* HVALENCE1		-3.33** (1.479)		-1.08 (1.384)		
ASC2* HVALENCE2		1.234 (1.450)		1.65 (1.517)		
ASC3*HVALENCE3		-0.98 (1.147)		3.80*** (1.434)		
ASC1* HLIKING1			0.31 (0.867)	1.18 (0.835)		0.63 (0.987)
ASC2* HLIKING2			0.26 (0.828)	0.138 (0.818)		0.60 (0.912)
ASC3* HLIKING3			2.41*** (0.922)	1.00 (0.897)		1.09 (0.896)
ASC1* HJOY1					-0.93 (1.119)	-2.20 (1.489)
ASC2* HJOY2					2.56* (1.448)	2.16 (1.526)
ASC3* HJOY3					2.87** (1.431)	3.12** (1.265)
ASC1* HCONTEMPT1					-1.78** (0.890)	-2.33* (1.189)
ASC2* HCONTEMPT2					-3.15*** (1.145)	-0.71 (1.072)
ASC3* HCONTEMPT3					-0.84 (1.142)	0.06 (1.155)
Number of participants	178	178	178	178	178	178
Number of observations	1,602	1,602	1,602	1,602	1,602	1,602
Log likelihoodfunction	-1,063.9	-1,061.3	-1 061.1	-1,060.5	-1 059.7	-1,052.2
AIC	2 149.8	2,144.6	2 144.2	2 149.1	2 147.5	2 138.4
BIC	2,208.9	2,203.8	2,203.4	2,224.4	2,222.7	2,229.8
McFadden pseudo R ²	0.52	0.52	0.52	0.52	0.52	0.53
Correct predictions (%)	45.69%	46.38%	46.25%	45.63%	46.01%	46.07%
In-sample validation (N = 100)	39.60%	44.87%	41.59%	44.16%	47.86%	41.17%
Out-of-sample predictions(%)	31.86%	32.89%	32.89%	34.21%	35.53%	34.21%

Notes.

^a ***, **, and * indicate p < 0.001, p < 0.01, and p < 0.05, respectively.

^b Standard errors in parentheses.

providing a brief talk may mitigate hypothetical bias in hypothetical DCEs, resulting in reliable results similar to those of non-hypothetical DCEs.

Comparing the fit of models M1, M2, and M3, model M2 had the lowest Akaike information criterion (AIC) and Bayesian information criterion (BIC), so it is the best statistical model. However, when comparing the fit of models M2, M4, and M5, model M5 was the best (lowest AIC, and lowest log-likelihood function). These results mean that model M5, which includes the hedonic score and the facial emotions, fits best our data. This supports previous research (Dalenberg et al., 2014; Gutjar et al., 2015), stating that the best predictions are achieved when combining both measures.

The results for models M1 and M3 show that participants expressing a more positive emotion toward the conventional wine ($HVALENCE1 > 0$) were less likely to select them; while the opposite occurred for vintage organic wine ($HVALENCE3 > 0$) where

consumers were more likely to select them. Models M2 and M3 point to a positive and significant relationship between high hedonic scores and overall valence (HVALENCE3) associated with the taste of selected organic wine (*HLIKING3*), and the choice of these wine types. This means that valence and hedonic scores were both good predictors for the choice of the selected vintage organic wine.

The results of models M4 and M5 show a positive relationship between higher joy (*HJOY*) and the choice of the organic wine and selected vintage organic wine and a negative relationship between contempt (*HCONTEMPT*) and the choice of the conventional and organic wine. In this particular setting, our findings illustrate that emotions are more relevant for new credence goods (organic wines) than traditional experience goods (regular wine).

As for the percent of correct predictions (predictions corresponding to the actual choices) of the models, these are very similar. Results of the in-sample prediction show that the model with immediate emotions *HJOY* and *HCONTEMPT* (M4) has the highest predictive power (47.86%). We also calculated the predictive power out-of-sample and results show that again the same model has the highest predictive capability (35.53%).

Results from model M6 (WTP estimates) are reported in Table 4. The results show that WTP for the three wine typologies are positive, highly significant, and similar to current market prices. WTP for the two organic wines are higher than that of the conventional wine. Compared to conventional wine, consumers are willing to pay a price premium (extra) of €1.87 and €1.73 for organic wine and selected vintage organic wine, respectively.

6. Conclusion

Economists consider consumers to often arrive at their decisions using a rational decision-making process. Over the years, behavioral economics and psychology have demonstrated that a large part of our decision is influenced by our emotional experiences.

Our paper presents an application to assess how emotions influence consumers' wine-purchasing decisions. Consumers' growing health concerns and environmental awareness have been increasing the demand for healthy and sustainable foods. This tendency provides a market opportunity for organic foods. This upward trend in demand has also been experienced in the wine industry, which is adopting organic production systems. Our paper has analyzed consumer interest in buying wines produced via different systems: conventional, organic, and selected vintage organic wines. It has evaluated whether and to what extent consumers are willing to buy organic and selected organic wines versus conventional wines.

Having in mind these research aims, we used a mixed research approach, combining a labeled DCE, a blind wine tasting, and a facial expression analysis. We measured facial expressions of emotions evoked by tasting different wine types (conventional, organic, selected vintage organic) using an innovative implicit method, and we incorporated these emotions into stated preference DCE models to improve our understanding and prediction of consumers' wine choices. The present work has assessed the role of emotions in wine choices, and we conclude that a positive relationship exists between valence and the choice of the selected vintage organic wine, and between joy and the choice of the selected vintage organic win. Overall, we find that experiencing positive and negative emotions has a greater influence on the choice of environmentally superior wines or wines with credence attributes. However, much remains unknown about the impact of emotions on overall choices and the best way to assess emotions. More evidence should be gathered to understand whether emotions place a more relevant role on the selection of credence goods. Moreover, we conclude that facial recognition mechanisms predict choices slightly better than actual hedonic liking scores. Future research should investigate why positive emotions influence only on the choice of specific attributes and the best way to measure emotions. Facial recognition and facial expressions are critical for better understanding economic behaviors. However, the economic literature has not yet evaluated this new way of perceiving emotions. Hence, we should pay attention to these innovative techniques by incorporating them into DCE and other valuation methods to better understand human behavior.

Funding

This work is part of the project "VINOVERT: Wines, competitiveness, environment and health policies of the companies in the SUDO area - support in implementing methodologies" [SOE1/P2/F0246], financed by the EU Research Program INTERREG SUDO.

CRedit authorship contribution statement

Djamel Rahmani: Conceptualization, Data curation, Formal analysis, Writing – original draft. **Maria L. Loureiro:** Supervision, Validation, Writing – review & editing. **Cristina Escobar:** Conceptualization, Data curation, Investigation. **Jose Maria Gil:** Conceptualization, Funding acquisition, Resources, Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests

Chema Gil reports financial support was provided by European Commission.

Data availability

Data will be made available on request.

Table 4
Willingness to pay estimates from WTP space.

	Average WTP	Standard deviation
Conventional wine	€3.70****	1.91***
Organic wine	€5.57***	2.55***
Selected vintage organic wine	€5.43***	2.67***

Notes.

^a ***, **, and * indicate $p < 0.001$, $p < 0.01$, and $p < 0.05$, respectively.

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